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Landing Gear Health Assessment: Synergising Flight Data Analysis with Theoretical Prognostics in a Hybrid Assessment Approach

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ABSTRACT

This study addresses a critical shortfall in aircraft landing gear (LG) maintenance: the challenge of detecting degradation that necessitates intervention between scheduled maintenance intervals, particularly in the absence of hard landings. To address this issue, we introduce a Performance Degradation Metric (PDM) utilising Flight Data Recorder (FDR) output during the touchdown and initial roll phases of landing. This metric correlates time-series accelerometer data from a Saab 340B aircraft's onboard sensors with non-linear response dynamic models that predict expected LG travel and reaction profiles across a set of ground contact cycles within a single landing. This facilitates the early detection of deviations from standard LG response behaviour, pinpointing potential performance abnormalities. The initiator of this approach is the Landing Sequence Typology, which systematically decomposes each aircraft landing into successive dynamic periods defined by their representative boundary conditions. What follows is the setting of initial parameters for the ordinary differential equations (ODE)s of motion that determine the orientation and impact responses of the most critical components of the LG assembly. Solving these ODEs with the integration of a non-linear representation of an oleo-pneumatic shock absorber model compliant with CS25 aircraft standards produces anticipated profiles of LG travel based on factors such as aircraft weight and speed at touchdown, which are subsequently cross-referenced with real accelerometer data, enhanced by video footage analysis. This footage is crucial for verifying the sequence of LG touchdowns and corresponding accelerometer outputs, thereby bolstering the precision of our analysis. Upon the conclusion of this study, by facilitating the early identification of LG performance deviations in specific landing scenarios, this diagnostic tool shall enable timely maintenance interventions. This proactive approach not only mitigates the risk of damage escalation to other components but also transitions main LG maintenance practices from reactive to proactive.

1. INTRODUCTION

Landing gear (LG) operational health is of paramount importance in ensuring aviation safety and optimising maintenance practices. Accurate assessment of LG component health can prevent catastrophic failures and reduce unscheduled downtime. Given the unique challenges posed by LG structural health monitoring (SHM)—arising from the use of high-strength, low-toughness materials in primary LG components, with relatively smaller critical crack propagation thresholds compared to the airframe—there is a compelling need for tailored monitoring approaches. A crucial constituent of LG SHM involves the monitoring of load, usage, and/or signs of crack initiation to estimate the remaining fatigue life of its monitored component/s. As a consequence, a prominent number of proposed LG health monitoring techniques rely on direct sensor placements, which can be intrusive, add weight, and increase the risk of error and maintenance requirements due to the introduction of said sensors. This study thereby addresses a prominent issue in the current LG integrity assessment approach followed by operators and MROs: the inability to detect LG degradation that requires intervention between scheduled maintenance intervals without the presence of hard landings. By inspecting touchdown and follow-up roll data at each landing cycle of the aircraft being monitored, we aim to remove the need for additional sensors. A Performance Degradation Metric (PDM) is being formulated, wherein the correlation of accelerometer time-series outputs with outputs from dynamic Ordinary Differential Equations (ODE)s of motion solved by Simulink models provides an indication of whether the LG's reaction profile was typical or deviant. This approach shifts the focus from identifying issues like structural cracks and bearing wear to detecting abnormalities through deviations in dynamic performance from the models derived from a distinct set of conditions under which the aircraft interacts with the ground, incorporating shock absorber behaviour, aircraft mass, and impact speed. Awaiting identical conditions for comparison would necessitate an impractical volume of test data and landings. Therefore, this strategy focuses on assessing how and to what extent each of these variables impacts each of the main LG's performance during each landing.

Data for this study were collected using the Cranfield University Saab 340B aircraft, operated by the National Flying Laboratory Centre. This twin-engine turboprop, known as the National Flying Laboratory, has been customised to include specific experimental and teaching equipment to enhance its utility as a flying laboratory. The key modification vital for this study is the installation of an Ekinox-D: An INS sensor that offers orientation, heave, and centimeter-level position accuracy.

The rest of the paper is organized as follows: Section 2 delves into the traditional and contemporary methods of LG maintenance, discussing the shift from time-based strategies to real-time health monitoring, illustrated through various studies and the integration of progressive monitoring systems like fiber-optic sensors. In Section 3, we outline our methodology, emphasizing the integration of video footage, on-board sensor data, and dynamic modelling to analyse aircraft landing dynamics. Data collection techniques and the specific analytics used to extract and process this data are also detailed. Section 4 projects the future direction of our research, outlining the subsequent phases including sensor data analysis, structural dynamic response assessment, and the continuous development of our Performance Degradation Metric (PDM).

2. Background

2.1. Traditional LG Maintenance Approaches

Traditionally, LG maintenance has leaned on time-based preventive strategies and Non-Destructive Testing (NDT) methods, including magnetic particle inspection, ultrasonic testing, and eddy current testing, as Schmidt (2008) notes. These conventional methods, applied during fixed maintenance intervals, often necessitate the disassembly of LG components for thorough inspection. In this context, the introduction of progressive monitoring marks a significant shift in maintenance paradigms. For instance, Kaplan et al. (1997) demonstrated the application of damage tolerance methods to extend the life of LG assembly subcomponents of a CASA 212 aircraft beyond their initial Safe-life design limits. By conducting loads, stress, and crack-growth analyses, they determined tailored inspection intervals. This approach underscores the potential of integrating damage tolerance principles to refine LG maintenance practices, paving the way for the adoption of landing profile-specific and load-adaptive health monitoring. Despite their intuitive approach and its success in extending the gear's service life, their methodology does not support real-time nor near-real-time assessment of LG health—a capability our current study seeks to develop. Importantly, while their approach contributes to extending the safe operational life of LG components, our project does not address direct estimations of life extension beyond set service limits, focusing instead on identifying and addressing immediate health concerns in operational conditions.

2.2. Advancements in Real-Time LG Health Monitoring

Building on these developments, recent advancements have shifted focus towards real-time LG health monitoring systems. These often involve the placement of sensors on critical LG components to monitor their condition during operation, such as that proposed by Zhang et al. (2018), who studied the placement of fiber-optic sensors on the outer tube weld of a LG assembly to capture weld crack signals. Further illustrating this trend, the EU-funded E-LISA project aims to develop an intelligent test facility for electro-mechanical LG, which will include PHM functionalities for the electrical brake system (De Martin et al., 2022). This project focuses on integrating sensors and monitoring systems into a novel LG design to enable condition-based maintenance. Similarly, Delebarre et al. (2017) contribute to the expanding landscape of sensor-based health monitoring with their development of a wireless monitoring system for lightweight aircraft LG, which uses pressure sensors and accelerometers to measure the mass distribution on each LG and monitor the shock during the landing phase. The system aims to provide real-time information to the pilot and maintenance personnel to improve safety and ease maintenance operations.

2.3. Data Analytics and Physics-Based Modelling in LG Health Monitoring

Integrating health monitoring systems into the LG architecture presents numerous challenges, such as coping with the harsh operational environment, managing the constraints on sensor placement, and ensuring the reliability of data transmission and analysis. These hurdles notwithstanding, the advancements in sensor technology and data analysis techniques offer promising pathways to surmount these obstacles, thereby enhancing the efficacy of aircraft LG health monitoring. In this vein, the work by (Bakunowicz & Rzucidło, 2020) presents an approach to detecting aircraft touchdowns using virtual sensing techniques by employing data from accelerometers mounted on structural parts of the airframe, utilising continuous wavelet transformation (CWT) to identify unique frequency signatures characteristic of LG touchdown. The CWT method, focusing on the detection of aircraft touchdowns with a high degree of precision, aligns closely with the present paper's emphasis on optimising aircraft sensor output for LG health assessment. By extracting critical frequencies from accelerometers on-board during touchdown, our approach seeks to isolate and analyse pre-impact signatures, enhancing the precision of our health assessment metrics. Another pertinent reference in the context of virtual sensing is the work of Hsu et al. (2022) and its continuation by Chang et al. (2023), where they harness Flight Data Recorder (FDR) accelerometer outputs from a fleet of aircraft to detect early signs of exacerbated LG shimmy, thus indicating potential degradation that could require maintenance beyond scheduled intervals. Their study covers the taxiing phase before take-off and following landing, employing machine learning (ML) to link accelerometer readings with maintenance records across various LG components. They subsequently predict potential faults with almost 100% accuracy on almost all LG subcomponents used in training their ML model based on expert input and extensive data from landing cycle-based maintenance actions recorded on those specific LG components. Our study, while also utilising accelerometer data, extends the analysis to include longitudinal accelerations and converges specifically on the dynamics of landing impact and the subsequent short roll period, used in this case to include jumps and consequentially the Landing Sequence Typology approach which thereby defines non-linear response models representing their corresponding periods, for a CS25 aircraft.

The development of physics-based models for LG dynamics and health prediction has garnered significant attention in the field of LG SHM. These models aim to capture the interactions between various LG components and the forces they experience during operation (Schmidt, 2021). Recent studies have furthered this endeavour, focusing on high-fidelity dynamic modelling, synthetic dataset generation, and the advancement of prognostic algorithms for enhanced predictive accuracy. Wu, Gu, and Liu (2007) have notably developed a Nonlinear Model Predictive Control (NMPC) algorithm for semi-active LGs, utilizing Genetic Algorithms (GA). This method demonstrates an enhancement in LG performance by optimising the damping characteristics at touchdown, validated through drop tests that confirm the simulation model's accuracy. The GA-based NMPC approach effectively addresses the complex nonlinear dynamics of semi-active LGs, ensuring optimal performance despite constraints like the control valve's rate and magnitude limitations. In our approach, unlike the empirical validation possible through drop tests as utilised by Wu et al. (2007), we navigate the absence of a drop-test rig by emphasizing the integration of real-world operational data and physics-based models to refine our simulation accuracy further. This is in line with Krüger and Morandini's (2011) emphasis on the critical role of numerical simulation in LG dynamics assessment. Their research highlights the significance of modelling LG's dynamic response to various load excitations, underscoring the importance of a comprehensive understanding of LG dynamics for safety and performance. Finally, De Martin et al. (2022) present the development of the E-LISA iron bird, an innovative test facility for LG systems that includes PHM functionalities for the electrical brake system. The E-LISA project aims to reproduce the dynamic loads on the LG during landing, taxiing, and take-off, as well as the real contact between the LG wheel and runway. This approach aligns with our research objective of integrating real-world operational data and physics-based models to refine simulation accuracy and develop a hybrid approach for LG health assessment. De Martin. et al. (2022) present a high-fidelity dynamic model of the test rig, which incorporates the effects of runway-irregularities. This model serves as a foundation for generating synthetic datasets representative of various operating conditions and degradation levels, facilitating the development of prognostic algorithms. Their approach is similar to our use of physics-based models to predict the degradation of LG performance over time, and it highlights the importance of incorporating realistic operational conditions and representative component interactions in the set dynamic equations used to represent the conditions of a landing.

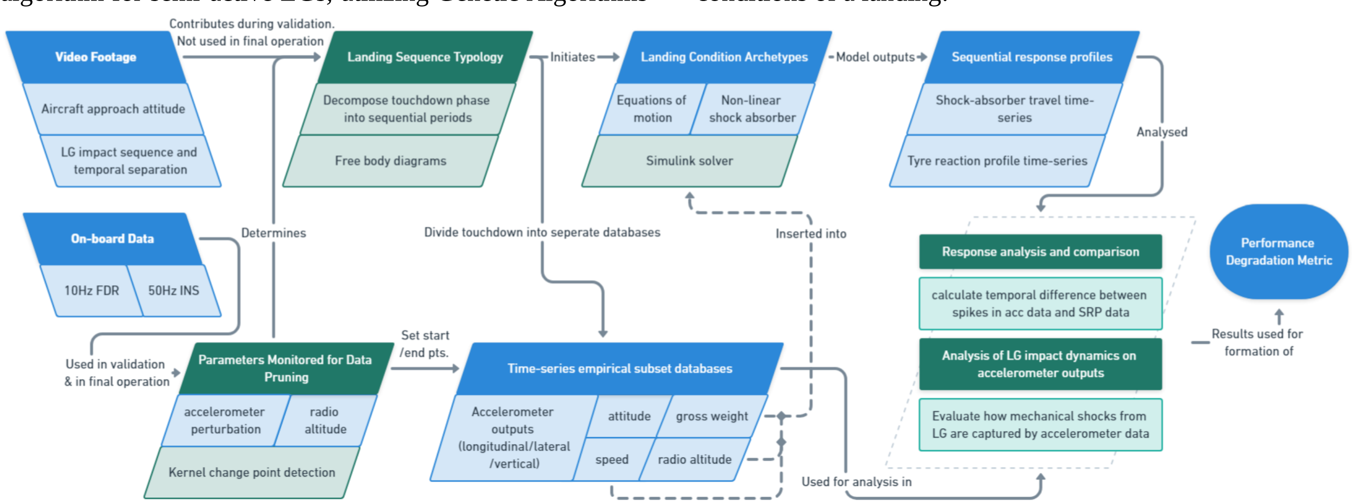

Figure 1. Integrated Framework for Aircraft Touchdown Analysis

3. METHODOLOGY

The methodology of this research is designed to analyse aircraft landing dynamics by integrating aircraft touchdown video footage, on-board sensor data, and bookcase non-linear response dynamic models, or ‘archetypes’, representative of the touchdown phases of each landing analysed. This multi-faceted approach allows for a robust examination of the impact sequences and a connection to the oleo-pneumatic shock-absorber (OSA) behaviours of the LG associated with different landing types. The study focuses on the following key aspects: capturing precise landing dynamics through video and sensor data, categorising landing types, formulating and solving ODEs to simulate these events, and validating these simulations against real-world data as feasibly as possible. Details follow in the subsections below, with corresponding visualisations provided in Figure (1), where the actions and outputs are denoted in green and blue blocks, respectively.

3.1. Data Collection

3.1.1. Video Footage Acquisition

A mirrorless APS-C video camera equipped with a telephoto lens is positioned on a fluid-head-equipped tripod by the runway border to record the final approach and touchdown. Operating at a frame rate of 29.97 fps and keeping the aircraft in-frame while extending the focal length to include only the undercarriage in the frame as soon as the aircraft is critically close to the airstrip, we ensure that each phase of the LG’s contact sequence with the runway is meticulously documented. To ensure clarity and precision in the footage, the camera's shutter speed is set to at least four times the frame rate. This serves two critical purposes: it counteracts the shutter roll effect noticeable during fast panning—important for preventing deformations in the objects in-video, affecting important parameters such as adding distortions to tire deformation, which would be misleading—and it minimises motion blur to capture crisp imagery (when inspecting each frame in the video) of exact moments of touchdown, spin-up, spring-back, and hop. Additionally, the ISO setting is carefully controlled to prevent excessive photo grain, which impairs the accurate identification of the wheel edges contacting the airstrip. This footage is crucial for visualizing the aircraft's attitude at approach and touchdown, and the temporal separation between all undercarriage units; the main right, main left, and nose gear contacting the runway. The video data serves two primary purposes: it provides a visual reference for validating sensor data (temporal OSA impact delivery to on-aircraft accelerometer response output) and helps in identifying any discrepancies between observed and simulated main LG assembly behaviours. In Figure (2), an example of the footage contents may be seen.

Figure 2. touchdown footage frame

3.1.2. On-board Data

The aircraft is equipped with an IMU as part of a custom fit Inertial Navigation System (INS); the Ekinox-D, operating at sampling rates of 50Hz. The onboard data acquisition takes place by the use of the Curtiss-Wright/ ACRA Control KAM-500 system, which collects analog data from the Saab 340B’s on-board sensors, including the Rockwell Collins AHS-3000 Attitude Heading Reference System. This setup captures essential aircraft dynamics and engine metrics using the Commercial Standard Digital Bus (CSDB) protocol (Alam, Whidborne, and Westwood, 2024). The data from these sensors are filtered to focus specifically on the touchdown phase, where detailed information about acceleration spikes and other dynamic responses is crucial for later analysis and simulation. The parameters recorded by these instruments include data on:

- Inertial Measurement Unit (IMU) and navigation: roll, pitch, heading, heave, surge, and sway from a MEMS (Micro-Electro-Mechanical Systems) sensor.
- Aircraft dynamics and engine metrics: accelerations, aileron and elevator deflections, angle of attack, fuel flow rates, gas generator speeds, propeller speeds, and turbine pressures.
- Environmental conditions: Airspeeds (indicated, true), Mach numbers, air temperatures, and radio altitudes.

In this study of aircraft dynamics, particularly before the initiation of gas generators and propellers, it is essential to calculate the root mean square (RMS) of accelerometer readings under stationary conditions. RMS is a statistical measure used extensively in signal processing to quantify the magnitude of a varying quantity. It provides a concise metric of the vibrational and transient accelerations experienced by the aircraft when it is static, which serves as a baseline for understanding the alterations in mechanical vibrations once the aircraft's propulsion components are activated. This baseline is critical for isolating and analysing the effects of mechanical and aerodynamic forces on the aircraft's structural integrity and operational efficacy. By calculating the RMS value of accelerometer data while the aircraft is stationary, we can establish a reference point against which deviations caused by the gas generators and propellers can be measured, thereby offering insights into the dynamic behaviour of the aircraft under different operational conditions. Below are the RMS values which show minimal deviations and reaffirm the trustworthiness of the accelerometers for our use case:

INS MEMS Sensor:

- Lateral Acceleration: 0.0199g
- Longitudinal Acceleration: 0.0049g
- Normal Acceleration: 1.026g (indicative of gravity's influence)

Aircraft's on-board accelerometers:

- Lateral Acceleration: 0.0046g
- Longitudinal Acceleration: 0.0015g
- Normal Acceleration: 1.026g

3.1.3. Parameters Monitored for Data Pruning

In this step, a subset of the original time-series data is created based on the critical time period for analysis. Here, the Gaussian kernel, synonymous with the Radial Basis Function (RBF), is pivotal in the field of kernel-based change point detection (KPD), offering a nuanced approach to analysing complex data patterns. Its efficacy proves useful as a part of our method when filtering the time-series accelerometer readings for point-of-touchdown. This algorithm was rigorously tested across numerous flights, to ensure consistent touchdown indications across all accelerometer axes. Seeking a universally applicable method across diverse flight profiles, the single-point RBF approach (dynamic programming) was used. This method, applied to the derivative of time-series accelerometer readings showed promising adaptability and accuracy. Providing start and end points close to a chosen cut-off of radio-altitude also reduces its computing requirements and is currently the chosen approach. In Figure (3), you may see a plot of accelerometer measurements, their derivatives, and a red dashed line running vertically along the plot, indicating the KPD output corresponding to point of touchdown for the landing aircraft.

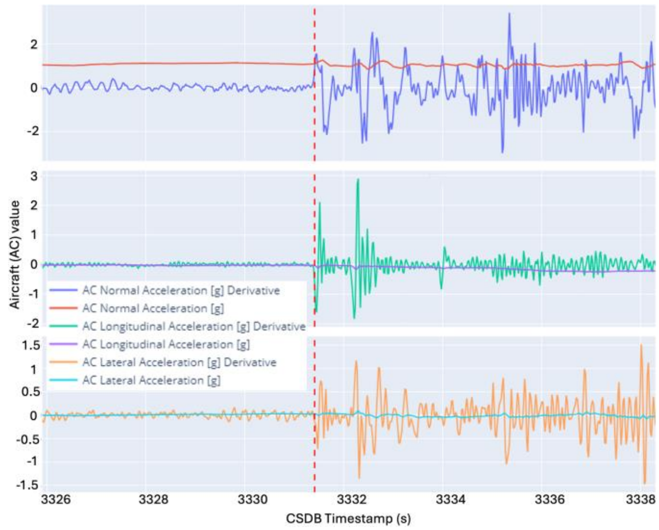

Figure 3. Accelerometer values and their derivatives w.r.t time for a level touchdown.

3.2. Landing Sequence Typology

To facilitate a structured analysis where causes and effects are recognised between landing load and landing variables, be they environmental, kinematics based, and/or temporal, each landing event is decomposed into several periods based on the amount of ground contact cycles. Each period is subsequently fitted to a category of distinct profiles based on observed dynamics and impact characteristics. The profiles are developed by analysing both video footage and sensor data to characterise each sequential landing period. This involves examining footage frames for the tyre impact timing, impact sequence, and the incidence angle, in addition to KPD-dictated touchdown indicators which serve in conjunction with the footage to dictate when the first period (linked to a profile) ends and the next begins. Each profile represents a set of initial conditions that are subsequently used to tailor the non-linear response archetypes. The profiles are categorised to be represented by, at their simplest:

- A smooth landing characterized by a negligible time difference between the touch-down of the rear right and left LG.
- High impact landings with minimal temporal separation between the rear LGs.
- Asymmetrical high impact landings affecting one side more than the other.
- Landings involving bounces, skips, or jumps.

By defining the characteristics of each period and linking it to a profile, the dynamic equations set for each profile can be adjusted to reflect the real-world dynamics observed during the data collection phase. This step ensures that they are representative of the variety of conditions the aircraft encounters in the duration of its single landing event.

3.2.1. Empirical Data Subsets Creation

Following the detailed decomposition of landing sequences as outlined in Section 3.2, and the rigorous data pruning mechanisms discussed in Section 3.1.3, the next phase focuses on compiling targeted time-series databases. These databases commence from the precisely determined touchdown point, leveraging the Gaussian kernel's efficacy in pinpointing this instant with high accuracy. The newly formed databases are confined to the parameters that are most indicative of landing dynamics and are crucial for the subsequent analysis:

- **Accelerometer Outputs**: Capturing the triaxial forces during the landing, these readings are pivotal for assessing the aircraft's response to touchdown dynamics.
- **Aircraft Attitude**: This includes the pitch, roll, and yaw of the aircraft at the point of touchdown, offering insights into the angular orientations that influence landing impacts.
- **Speed**: Ground speed and airspeed are included to correlate the velocity at touchdown with the landing impact severity.
- **Gross Weight**: The total weight of the aircraft influences the impact force and is thus critical for understanding the stress distribution on landing gears.
- **Radio Altitude**: For confirming the moment of touchdown and aids in synchronising other data streams.

Each database subset is tailored to represent a single impact cycle, which is identified based on the landing sequence typology. This approach ensures that each dataset is representative of specific landing conditions, thereby allowing for a more granular analysis of landing dynamics.

The speed, gross weight, and radio altitude are inserted into the completed landing condition archetypes for an output of the sequential response profiles that would allow for comparisons with the original subset databases containing the additional parameters representative of the period being inspected.

3.3. Landing Condition Archetypes

The preceding step, landing sequence typology, carries us closer to accurately representing the dynamics of a landing event by segmenting it into distinct sequential periods. Each period is tailored with specific boundary conditions corresponding to a respectively identified landing profile, enhancing the ground truth of our simulations, herein referred to as ‘archetypes’ which consist of non-linear dynamic ODEs combined with a model of a CS25 aircraft’s shock absorber and its interaction with the tyre and aircraft mass at level landing, which are critical for characterising the physical response of the aircraft's landing gear system under load. Given the lack of physical drop test rigs for empirical validation, it is imperative to assess the fidelity and robustness of these models.

Validation occurs in a bifurcated approach: Initially, the fidelity of the physics-based Simulink model is confirmed to ensure alignment between simulated performances with actual aircraft landing observations. This verification leverages detailed video stream analysis and FDR accelerometer data, which guide the establishment of stringent constraints and operational requirements specific to the landing gear system components in the simulation. These requirements are grounded in recognized benchmark methods, such as implementing damping strategies to mitigate resonance phenomena like shimmy and gear walk in the simulated landing gear assembly. A critical damping target, as stipulated by SAE International (2017) is reducing system oscillation to no more than a third of its original amplitude within three oscillation cycles post any perturbation.

3.3.1. Sequential Period Differential Equations

Using the data derived from the landing profiles, a set of ODEs is devised for each scenario. Free body diagrams (FBD) are utilised prior to forming these equations, ensuring that all relevant forces and interactions are accurately represented. The FBD of a level landing can be seen in Figure (4). These equations consider the mass, damping characteristics, and stiffness of the aircraft’s LG and structure. They include the non-linear characteristics of a CS-25 aircraft shock absorber, the interaction between the LG and the runway surface, and the effects of tyre dynamics on the LG system performance.

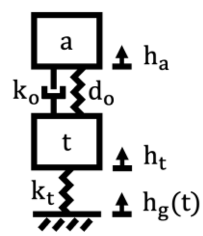

Figure 4. FBD for a level landing

The Simulink model in Figure (5) is adapted from that provided by (Jan R. Wright & E. Cooper, 2014). Simulink's environment allows for the continuous adjustment and real-time simulation of the equations, facilitating an iterative process of model refinement. The system is broken down into the aircraft rigid body mass and tyre mass, each with their own set of ODEs. The aircraft mass ODE includes terms for the spring and damper forces connecting the aircraft and tyre. The tyre mass ODE considers the forces from the OSA spring and damper, the tyre spring force, and runway height profile. A simple rigid aircraft landing system, assuming lift equals weight at touchdown, and ignoring spin-up and spring-back and resulting LG motion due to them, is broken down as follows. Given:

- $\boldsymbol{h_a}$: Height of the aircraft mass from a reference point.
- $\boldsymbol{h_t}$: Height of the tyre mass from the same reference point.
- $\boldsymbol{h_g(t)}$: Runway height from the reference point, which is a function of time.
- $\boldsymbol{k_a}$: Spring constant connecting aircraft and tyre.
- $\boldsymbol{d_a}$: Damper constant connecting aircraft and tyre.
- $\boldsymbol{k_t}$: Spring constant connecting tyre and ground.

The resulting ODEs for the aircraft and tyre mass, respectively, are in Eq. (1) and Eq. (2) below:

$$m\ddot{h}_a = -k_a(h_a - h_t) - d_a(\dot{h}_a - \dot{h}_t) \qquad (1)$$

$$m_t\ddot{h}_t = k_a(h_a - h_t) + d_a(\dot{h}_a - \dot{h}_t) - k_t(h_t - h_g(t)) \quad (2)$$

Additional ODEs are introduced for pitch and yaw dynamics depending on the period profile being modelled, considering the aircraft's moments of inertia, aerodynamic moments, and LG forces, and are a work-in-progress.

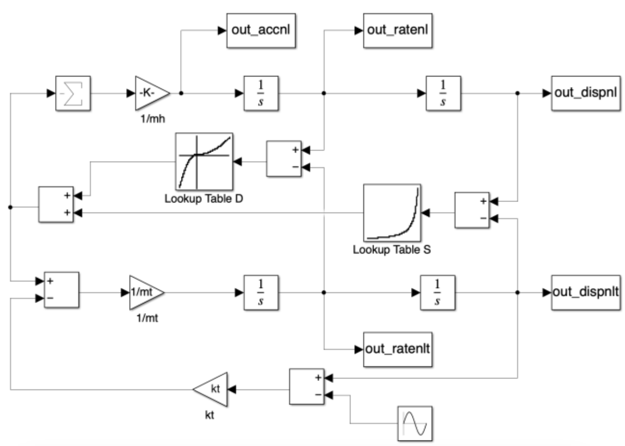

Figure 5. Simulink representation for a rigid-body level aircraft landing on main landing gear.

3.3.2. Non-linear Oleo-Pneumatic Shock Absorber

The OSA modelled employs a gas spring mechanism (the integral part affecting its dynamics), where the dynamics are significantly influenced by changes in gas volume and pressure during landing impacts. Its functionality is governed by the Ideal Gas Law, expressed as $PV^\gamma = C$, where P represents the absolute pressure, V the volume of the gas, γ the polytropic constant, and C a constant. The value of γ varies based on the OSA's operational conditions:

- Static Conditions (γ=1): This scenario represents steady, slow compressions such as during taxiing, where the temperature is maintained constant due to sufficient time for heat transfer.
- Dynamic Conditions (γ=1.3−1.4): During rapid compressions, such as landings, the process is adiabatic with no heat transfer, reflecting a higher γ value.

During the OSA's operation, as the LG encounters forces from the runway, the piston compresses, altering the gas volume. For a given change in volume ΔV caused by the piston stroke z, the new volume V_2 is given by $V_2 = V_1 - Az$, where A is the piston area. The corresponding pressures before and after compression, from the fully extended state V_∞ to the compressed state V_c are linked by Eq. (3):

$$P_\infty {V_\infty}^\gamma = P_c(V_\infty - Az)^\gamma \qquad (3)$$

The absolute pressure/displacement relationship can then be expressed in Eq. (4), where z_∞ is the fully bottomed distance (Jan R. Wright & E. Cooper, 2014):

$$\left(\frac{P}{P_\infty}\right) = \left(1 - \frac{z}{z_\infty}\right)^{-\gamma} \qquad (4)$$

According to Currey (1988), the typical characteristics for these calculations are as follows:

- Piston Area (A): Depends on the static pressure in the shock absorber, e.g., A=0.005m^2 if $P_{\text{static}} = 100$ bar.
- Pressures: $P_c = 3P_{\text{static}}$ and $P_\infty = 0.25P_{\text{static}}$.
- Volume Ratios: Assuming $V_\infty/V_c = 12$, then $V_\infty = V_c + A \cdot z_{\text{static}}$.

During landing, assuming that the lift equals the weight of the aircraft and neglecting tyre deformation to simplify the energy considerations, the kinetic energy of the aircraft equates to the work done by the OSA as in Eq. (5) (Jan R. Wright & E. Cooper, 2014):

$$\frac{1}{2}mv_y^2 = \eta_{\text{SA}}F_{\text{LGmax}}z_s = \eta_s\eta_{\text{LG}}Wz_s \qquad (5)$$

Where:

- m : Mass of half the aircraft plus part of the landing gear above the OSA.
- η_{SA} : Efficiency of the OSA, typically around 0.8.
- η_{LG} : LG load factor, ranging from 2 to 2.5 for CS-25 aircraft, representing the ratio of (static + dynamic reaction load) to (static load).
- W : Weight of the aircraft, equal to mg.

The force generated by the OSA, which is crucial for mitigating the impact during landing, is a function of the pressure differential across the piston. This force contributes to the overall dynamics of the aircraft's LG by opposing the landing load and dissipating kinetic energy. This is then translated into the Simulink environment through a series of blocks representing the aircraft's landing dynamics. The forces calculated from the OSA's pressure and volume changes are fed into the model to simulate the periods within the real-time landing event. These blocks use look-up tables generated from the aforementioned theoretical calculations.

3.3.3. Sequential Response Profiles

Sequential response profiles are derived from the outputs of the Simulink model to assess the performance of the OSA and the travel behaviour of the main LG during each sequential period. These profiles are essential for evaluating what similarities can be inferred between the archetypes and the empirical subset time-series data. The response profiles include the shock-absorber travel time-series, which tracks the displacement and normalised load absorbed over time, and the tyre reaction time-series, documenting the reaction forces of the tyre which reflect the dynamics of the unsprung mass. The analytical approach involves aligning the data starting at the moment of touchdown, identified by radio altitude and verified through accelerometer data, ensuring that the simulation phases are synchronized with the actual event timings. The Simulink solver continuously processes the differential equations representing the landing dynamics. The shock-absorber's travel and tyre reaction forces are methodically captured and plotted to provide an examination of the forces at play during the landing.

3.4. Comparison with On-board Data

In parallel, while video footage is used to validate the temporal and sequential accuracy of the archetypes in some capacity, the sequential response profiles (Simulink outputs) are compared to the time-series empirical accelerometer output corresponding to each of these periods. In our study, the primary objective of comparing Simulink model outputs to empirical accelerometer data is to establish a robust relationship in terms of observed trends and to correlate these observations with specific landing profiles, such as a hard level landing. This analysis involves comparisons of both Simulink outputs and accelerometer data collected from the aircraft during defined landing scenarios. The goal is to systematically expand this analysis across multiple flights and varying initial conditions, thereby compiling a comprehensive set of correlations between the model's predictions and the actual accelerometer responses recorded on the aircraft. For each period of each landing event analysed, the model outputs and accelerometer readings are compared to determine how closely the simulated responses (from the Simulink model) align with the real-world data under similar operational conditions. Key parameters considered during these comparisons include aircraft speed, gross weight, and radio altitude variation which would give us vertical speed at the point of touchdown. Through repeated evaluations across diverse flight conditions, this method allows us to refine our understanding of the dynamic interactions between the aircraft's LG and the runway surface.

3.5. Performance Degradation Metric Definition

As the dataset grows, encompassing a wider array of flight profiles, we progressively build a Performance Degradation Metric (PDM). This metric is designed to assess, using only the time-series output from the aircraft's accelerometers at touchdown, whether the observed accelerometer responses align with expectations derived from our simulations and previous correlations. This involves two critical analyses: first, evaluating the output of the Simulink model corresponding to the given profile (in the form of sequential response profiles for the specific period), and second, examining the established relationships between key accelerometer performance indicators, including peak-to-peak time, temporal peak separation, and time interval analysis relative to specific thresholds, and their alignment with Simulink model outputs. Based on the discrepancies identified between the simulated results and the actual data, adjustments are made to the ODEs and their parameters in the Simulink model. These adjustments may include changes in the damping coefficients, stiffness parameters, and mass distribution within the landing gear system. Each iteration aims to reduce the error margin and enhance the fidelity of the model. This approach aims to ensure as much as possible that each phase of the investigation contributes to a systematic and scalable understanding of the landing dynamics, which is crucial for advancing the predictive capabilities of our models.

Central to the separation in terms of model comparison of this analysis is the delineation of the minimal interval necessary for both main LGs to contact the runway simultaneously in a level touchdown—a scenario that equally distributes the landing load but remains exceedingly rare due to the imperative for pilots to adjust for crosswinds through controlled bank angles and the inherent inconsistencies present in airstrip surfaces. In recognising that aircraft landings may encompass a complex combination of the aforementioned scenarios, the PDM shall incorporate a nuanced measurement of the intensity and category of each phase encountered, leading to the point of analysing probability of performance degradation; assessing each LG unit's potential for operational wear (be it the right or left LG assembly). By continuously refining the correlation between simulated outcomes and actual flight data, our study aims to provide reliable predictive tools that can effectively anticipate operational degradation of the aircraft's landing systems under varied operational conditions.

This PDM is to output a relative operational health status of the main LG assemblies as shown in Figure (4). This plot displays the relative operational health status of the main LG assemblies over the course of successive landings. The initial operational health status is set at 100% at the commencement of operation (0 landings), with the Safe-life indicating the theorised lifespan, shown as a fixed endpoint in the plot at a landing life of 60k. The plot simplistically portrays the relative operational health as declining linearly; however, this does not reflect real-world conditions and is merely a simplification for illustrative purposes. The plot serves as a theoretical model, illustrating the projected outcomes we aim to achieve by the conclusion of the project. Key components include:

- **Safe Life Health Status**: The dashed red line serves as a theoretical performance threshold. Should the operational health of any LG assembly drop below this line, as predicted by the hybrid model, this would suggest potential risks at which an inspection is required.
- **Left and Right LG Hybrid Approach Health Status**: The blue and green lines show actual health status tracking for left and right LG, respectively, with maintenance actions represented by ‘x’ markers.
- **LG Failure at 5400 Landings**: This trend exemplifies the characteristic decline preceding a failure event.
- **LG Health in Ideal Low Wear Conditions**: A trend representing a LG assembly that has undergone extremely low-impact landing cycles.

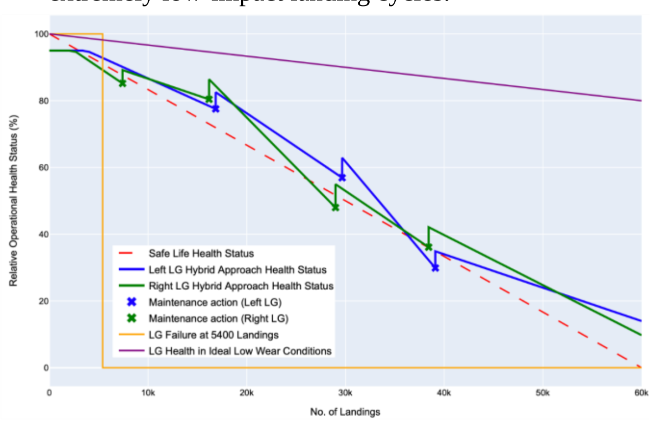

Figure 6. LG Operation Health Status

The value of the relative operational health status represents the current operational condition of the system, rather than direct LG part degradation. Its value is relative to the corresponding value of the Safe Life Health Status at that no. of landings. In Figure (7), a closer examination of the initial segment of the plot in Figure (6) reveals inherent uncertainties in the model's operation, stemming from the requisite number of landing cycles needed to establish reliability. Currently, this figure is illustrative and subject to refinement as our project evolves towards more precise and realistic estimations.

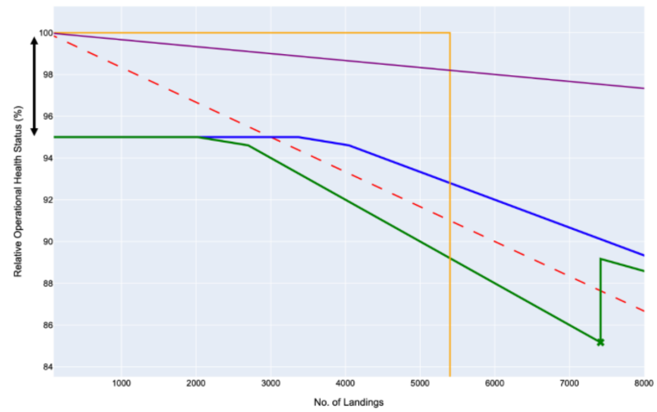

Figure 7. A close-up on no. of landings required for model validity

4. PROJECT DIRECTION AND FUTURE WORK

This paper marks the commencement of a structured approach for enhancing LG health assessments by means of virtual sensing combined with landing scenario-representative empirical models. While this paper discusses the initial stages of the first study, subsequent planned investigations will further this exploration:

Study 1 - Sensor Data Analysis and LG Dynamics: This segment focuses on extracting and analysing data from the FDR and IMU, comparing these to LG response profiles that are a result of landing condition archetypes to detect deviations in accelerometer oscillations and other critical parameters. Objectives include:

- **Operational Condition Analysis**: Examining variations in LG dynamics across different operational conditions.
- **Performance Pattern Identification**: Identifying desirable performance patterns and recognising limitations.

Study 2 - Sensor Placement and Data Precision: This study aims to compare IMU and on-aircraft accelerometer outputs during the landing's touchdown and roll phases, to identify the most effective sensor placements for LG response evaluation. This assists in pinpointing LG performance patterns during crucial phases. The focus areas are:

- **Sensor Output Comparison**: Crafting strategies for comparing sensor outputs to underline strategic placement.
- **Filtering Techniques**: Applying filtering methods to sensor outputs for improved data accuracy.

Study 3 - Structural Dynamic Response: Initiates a quantitative examination of modal frequencies and structural resonances before landing, employing high-fidelity spectral analysis to differentiate these from frequencies observed post-touchdown. This study encompasses high-fidelity spectral analysis to separate pre-impact from post-impact frequencies.

Results and Future Directions: Following these studies, we shall present:

- **PDM Development**: A more detailed discussion on the development and validation of the PDM, including an assessment of operational degradation in the port and starboard LG relative to maintenance schedules.
- **Empirical and Theoretical Insights**: A comparative analysis offering essential insights from our empirical data and theoretical models.
- **Case Studies**: Application of our hybrid approach to real-world scenarios.

Future initiatives will broaden these methodologies to encompass more aircraft components and scenarios, aiming to reduce aircraft downtime and enhance safety across various models.

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Landing gear health assessment: synergising flight data analysis with theoretical prognostics in a hybrid assessment approach

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